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Return Predictability: The Dual Signaling Hypothesis of Stock Splits

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Abstract

This paper aims to differentiate between optimistic splits and overoptimistic/opportunistic splits. Although markets do not distinguish between these two groups at the split announcement time, optimistic (over-optimistic/opportunistic) splits precede positive (negative) long-term buy-and-hold abnormal returns. Using the calendar month portfolio approach, we show that the zero-investment, ex-ante identifiable, and fully implementable trading strategy proposed in this paper can generate economically and statistically significant positive abnormal returns. Our findings indicate that pre-split earnings management and how it relates to managers' incentives, is an omitted variable in the studies of post-split long-term abnormal returns.

Keywords: Stock Splits, Earnings Management, Long-term Stock Returns, Dual-signaling Hypothesis.

JEL classification: G11, G12, G14, G35, M41.

1. Introduction

Since the seminal work of Fama, Fisher, Jensen, and Roll (1969, henceforth, FFJR), the finance literature provides several alternative explanations for conducting a stock split. A manager can conduct a stock split to signal positive private information (Lakonishok and Lev, 1987; McNichols and Dravid, 1990; Desai and Jain, 1997), to lower a stock price to a preferable range (Lamoureux and Poon, 1987; Dyl and Elliott, 2006), and to boost stock liquidity (Muscarella and Vetsuypens, 1996; and Lin, Singh, and Yu, 2009).[1] However, Weld et al. (2009) argue that none of these explanations actually justify conducting a stock split. In order to further explore the signaling hypothesis, recent papers have investigated the dual use of a stock split and earnings management. For example, Louis and Robinson (2005) argue that combining a split and discretionary accruals may be an effective means of communicating managers' private information, rather than a means of deceiving shareholders. They state that "the stock split signal lends credibility to the accrual signal whereas the accrual signal reinforces the split signal." [2] By contrast, Guo, Liu, and Song (2008) argue that managers support their already inflated stock prices (due to aggressive earnings management) by announcing stock splits. They argue that managers use that approach to delay stock price corrections before stock-financed acquisitions. The extant literature on stock split return predictability does not differentiate between announcement and/or long-term returns of optimistic splits (Louis and Robinson, 2005) and opportunistic splits (Guo, Liu, and Song, 2008). This paper aims to contribute to this gap in the stock split return predictability literature.

[1] Another explanation for the use of stock splits is the desire of companies to supply shares at lower prices when investors are more willing to pay premiums for cheaper stocks. For a comprehensive review of different motives for stock splits, please see Minnick and Raman (2014).
[2] See Louis and Robinson (2005). PP. 361.

Investigating the dual use of stock splits and earnings management, and its implications on the announcement as well as long-term split returns would enable us to better understand market reaction to different types of splits and to better understand results in the prior literature.

In this paper, we try to differentiate between two groups of stock splitters. The first group (optimistic splitters) consists of firms that conduct stock splits without a high degree of earnings management to convey positive private information. The second group (overoptimistic/opportunistic splitters) consists of firms that combine stock splits with a high degree of earnings management as a reflection of overestimation of, or to send a false signal about, future earnings streams. Specifically, we use the degree of pre-split earnings management (through both discretionary accruals and real activities management [RAM] measured by abnormal cash flows) as a differentiating factor between these two groups of stock splits. Our results show that investors do not differentiate between these two types of stock splits at the time of the announcement. However, these two types have strikingly different long-term returns. Splits conducted by optimistic firms are followed by significantly positive long-term abnormal returns. By contrast, splits conducted by overoptimistic/opportunistic firms are followed by significantly negative long-term abnormal returns. To the best of our knowledge, this paper provides the first empirical evidence that long-term returns are significantly negative for an ex-ante identifiable group of stock splits.

Using tercile double ranking, we construct nine portfolios of stock splits ranked based on the degree of earnings management (henceforth, portfolios M1: M9). Portfolio M1 includes firms in the bottom discretionary accruals and RAM terciles prior to a stock split. At the other extreme, portfolio M9 includes firms in the top discretionary accruals and RAM terciles prior to a stock split. We argue that portfolios at the top of this ranking are more associated with managerial over-optimism/opportunism while portfolios at the bottom of this ranking are more associated with managerial optimism. We first investigate whether investors differentiate between optimistic splits and overoptimistic/opportunistic splits at the time of the split announcement. Our results indicate that investors do not differentiate between these two groups of splits at the time of the announcement. Inversely, there is weak evidence that investors have a better reaction to overoptimistic/opportunistic splits. This evidence is consistent with Louis and Robinson (2005).

Next, we investigate the long-term returns of optimistic splits and overoptimistic/opportunistic split. The main premises of this paper are that optimistic splits are expected to be followed by positive abnormal returns while overoptimistic/opportunistic splits are expected to observe return reversals in the post-split period. Our buy-and-hold abnormal returns (BHAR) results show that the one-year BHAR for portfolio M1 is 5.5 percent, a figure in stark contrast to that of portfolio M9 which has a one-year BHAR of -16 percent during a comparable period. In addition to using the BHAR approach, we test our conjectures using the calendar month portfolio analysis. Results of the calendar month analysis show that the equally (value) weighted zero-investment portfolio that buys portfolio M1 and sells short portfolio M9 would gain 100 (90) basis points per month for a 12-month holding period.

Since earnings management estimates are mandatory for our portfolio formation, the use of split events conducted before the release of annual reports would create a look-ahead bias in our results. So, to ensure that our proposed strategy is fully implementable and to avoid the look-ahead bias issue, we exclude all splits announced within several annual report release periods (45, 60, and 75 days after the fiscal year end). This filtration does not hinder the profitability of the calendar month trading strategy.

We interpret our findings as empirical evidence on the dual use of stock splits and earnings management as a signaling strategy. However, prior literature provides several alternative explanations to stock splits in addition to the signaling hypothesis. We conduct additional tests to rule out the possibility that splits identified as overoptimistic/opportunistic in this study are explained by changes in households' ownership and/or institutional ownership, liquidity, and catering to investors' desire to buy cheap stocks. Further, we show that CEOs who conduct these splits (splits identified as overoptimistic/opportunistic in this study) engage more in insider trading around split announcements, lending further support to the signaling explanation.

To highlight the possibility of using our portfolio formation to better explain results in the prior literature, we replicate the test in Byun and Rozeff (2003), that shows that, during the 1991-1996 period, long-term returns following stock splits are not significantly different from zero.[3,4] Our BHAR results during that period are similar to Byun and Rozeff (2003) for the overall stock split sample. However, when we use our portfolio ranking, we report statistically significant negative (positive) abnormal returns for portfolio M9 (all other splits). These results can help better explain the zero-abnormal return evidence reported in Byun and Rozeff (2003).

Further, we conduct several tests to check the sensitivity of our results to factors that have been shown to impact long-term return predictability following stock splits. To check the impact of information asymmetry, we examine the profitability of our trading portfolio for subgroups of large and small firms. To check the impact of dividends, we test the profitability of our trading

[3] Required earnings management data is not available to replicate the sample period of FFJR (1969) or Desai and Jain (1997), who test long-term returns following stock split using 1927-1950 period and 1976-1991 period, respectively. We have earnings management data to test the results of Byun and Rozeff (2003) that abnormal returns are not significantly different from zero for splits announced during the 1991-1996 period. This test is reported in section 4.2.5.

[4] Byun and Rozeff (2003) start their measurement after the split effective date instead of the split announcement date (Boehme and Danielson, 2007).

portfolio for subgroups of dividends payers, non-dividends payers, firms that simultaneously increase dividends and conduct a stock split, and firms that do not simultaneously increase dividends with stock splits. To check the impact of institutional ownership, we test the profitability of our trading portfolio for firms with high and low institutional ownership. Our results rule out the possibility that these factors drive abnormal returns results reported in this paper. Further analysis shows that the profitability of our proposed portfolio did not disappear after the Sarbanes Oxley Act (SOX). We also test the sensitivity of our results to alternative RAM mechanisms such as cutting discretionary expenses. Our results do not change when we use growth and performance-adjusted discretionary accruals (Collins, Pungaliya, and Vijh, 2016). Lastly, our results are robust for value and glamour stocks, and for subgroups of firms with different splitting factors (splits with a 2:1 factor vs. other splits). All our tests use variables that are winsorized at the 1 and 99 percent levels; however, our results do not change when we use unwinsorized variables (Kraft, Leone, and Wasley, 2006; Kothari, Sabino, and Zach, 2005).

This study makes several contributions to the literature. Our results contribute to the signaling literature by further investigating the practice of combining signals and tactics that managers might use to convey private information, or alternatively to deceive shareholders. To the best of our knowledge, this paper provides the first empirical evidence that long-term returns following stock splits are systematically negative for an ex-ante identified group of firms. Our findings provide insights in explaining the contradicting findings in the literature about post-split return patterns. Further, this paper complements Louis and Robinson (2005) and contributes to the earnings management literature by showing that the duality of earnings management and stock split is not always a signal of managerial optimism but instead could reflect managerial over-optimism and/or opportunism. The essence of our results is similar to Fuller (2003) who shows a variation in dividend price reactions that is linked to characteristics of pre-announcement trading activity. Similarly, this paper shows a variation in stock split price reactions that is linked to characteristics of pre-split reported earnings.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 presents data and research methods. Section 4 presents analysis and results. Section 5 presents additional robustness tests, and section 6 concludes the paper.

2. Literature review

Stock splits have always presented a challenge to the efficient-market hypothesis. If markets are not efficient concerning this basic event (that has minimal cash flow consequences), then the efficient-market hypothesis is even more questionable regarding more informative events such as earnings announcements and seasoned equity offerings (SEOs). The importance of stock splits resulted in a large stream of papers trying to understand the motives behind splits as well as the short-term and long-term market reaction to split announcements. This literature provides several explanations for stock splits; the optimal trading range hypothesis posits that a manager can conduct a split to lower a stock price to a preferable range (Lamoureux and Poon, 1987; Maloney and Mulherin, 1992; Dyl and Elliott, 2006). A manager can also conduct a split to boost stock liquidity (Muscarella and Vetsuypens, 1996; Lin, Singh, and Yu, 2009). Further, the signaling hypothesis asserts that a manager can conduct a stock split to signal positive private information (Brennan and Copeland, 1998; Lakonishok and Lev, 1987; McNichols and Dravid, 1990; Desai and Jain, 1997). The signaling hypothesis is consistent with the seminal work of FFJR (1969) who state that “a split, which implies an increased expected dividends, is a signal to the market that the company’s directors are confident that future earnings will be sufficient to maintain dividend payments at a higher level.”

More recently, several papers investigate the signaling hypothesis regarding stock splits when combined with earnings management, i.e., the dual signaling effect of a split and earnings management. For example, Louis and Robinson (2005) argue that managers can use accruals in conjunction with other positive signals, such as stock splits, to enhance the credibility of accruals as a means of signaling favorable private information. Inversely, Guo, Liu, and Song (2008) argue that managers combine the split signal and the earnings management signal to deceive investors before stock-financed acquisitions. The opportunistic use of stock splits (as described in Guo, Liu, and Song [2008]) is also consistent with the optimal trading range hypothesis. According to Grinblatt, Masulis and Titman (1984, henceforth, GMT), one of the main disadvantages of the optimal trading range hypothesis is that managers of some overvalued firms might split simply to obtain a temporary stock price increase and delay stock price correction.[5]

These two explanations for the dual use of a split and earnings management are related to the two explanations for earnings management provided by the accounting literature. On one hand, managing earnings is usually perceived as opportunistic behavior aiming at misleading investors. Furthermore, there is consistent evidence of a negative relationship between pre-event discretionary accruals and post-event abnormal returns.[6] On the other hand, other studies posit that managers sometimes use their reporting discretion to signal their private information (Subramanyam, 1996; and Guay, Kothari and Watts, 1996). In that regard, Healy and Wahlen (1999) argue that most researchers test managerial reporting discretion in contexts in which managers are more likely to display opportunistic behavior. Guay, Kothari, and Watts (1996) also

[5] Devos, Elliott, and Warr (2015) also highlight the possible opportunistic use of stock splits.

[6] For example, for seasonal equity offerings (Teoh, Welch, and Wong, 1998b), management buyouts (Perry and Williams, 1994), initial public offerings (IPOs) (Teoh, Welch, and Wong, 1998a; and Shivakumar, 2000), stock-for-stock mergers (Erickson and Wang, 1999; and Louis, 2004), repurchase announcements (Gong, Louis, and Sun, 2008), and annual general meetings (Banko, et al., 2013).

recommend that researchers should take managers incentives into consideration when studying the opportunistic hypothesis versus the signaling hypothesis of managerial reporting discretion.

As a result, the tactic of combining earnings management signals and split signals could be performed by several types of managers: first, optimistic managers, as described in Louis and Robinson (2005), who have positive private information and who split their stocks to support their accruals signal; second, opportunistic managers, as described in Guo, Liu, and Song (2008), who aggressively manage earnings for manipulative purposes and who split their stocks to support their false reporting signals; and third, overoptimistic managers, who would manipulate earnings to levels not warranted by their weak future earnings (Schrand and Zechman, 2012), but who would also split their stocks to convey "what they believe" to be favorable private information.

We argue that differentiating between these groups of splits cannot be performed solely by observing pre-split discretionary accruals, which could be growth-triggered (Collins, Pungaliya, and Vijh, 2016) and/or associated with managerial optimism (Louis and Robinson, 2005). The use of RAM to complement accruals management might provide a differentiating factor between the abovementioned groups of stock splits. Although some optimistic managers could participate in either discretionary accruals management or RAM and thus leads to the weakening of their stand-alone return predictability, the concurrent use of aggressive discretionary accruals and RAM is more likely to be associated with over-optimism and/or opportunism (Cohen and Zarowin, 2010; Hsieh, Bedard, and Johnstone, 2014).

In the long run, actual private information is revealed to the market, and while optimistic splitters should experience positive returns, both opportunistic and overoptimistic splitters should experience return reversals. Prior studies on return predictability following stock splits do not recognize the existence of opportunistic or overoptimistic splitters.[7]

It is worth noting that the distinction between overoptimistic splits and opportunistic splits is beyond the scope of this paper. Instead, this study focuses on distinguishing between optimistic splits on one hand and overoptimistic/opportunistic splits on the other hand, and the possibility of using this distinction to predict long-term abnormal returns following stock splits. Further, this paper does not aim to test the accruals anomaly or the RAM anomaly per se. Instead, our results highlight the importance of taking managerial incentives into consideration when studying signaling hypotheses and/or managers' use of combined signals.

3. Data and methodology

3.1. Data

Our study starts with the entire sample of forward stock splits that took place during 1988–2011 on NYSE, AMEX, and NASDAQ.[8] Our sample includes stock splits conducted by ordinary stocks, so we exclude splits conducted by American depositary receipts (ADRs), real estate investment trusts (REITs), small business institute (SBIs), and closed-end funds. We retrieved stock returns data from the Center for Research in Security Prices (CRSP), and financial and accounting data from COMPUSTAT. Our final sample consists of 5,155 stock split events during the 1988–2011 period.[9]

[Please insert Table 1 here]

[7] See for example Ikenberry and Ramnath (2002) and Chemmanur, Hu, and Huang (2015).

[8] Desai and Jain (1997) show that their results are not different between the sample of stock splits and the sample of large stock dividends. So we do not distinguish between these two groups in our study.

[9] Please notice that, in order for a stock split to be included in our final sample, data should be available to estimate both abnormal cash flows and discretionary accruals. This condition reduced the sample size from 11,427 to 5,155.

Table 1 provides descriptive statistics for our final sample. Panel A reports the number of splits per year. Split events are well distributed over the sampling period; however, there are a relatively higher number of stock splits during bull periods such as the late 1990s. After the financial crisis of 2008, the number of splits significantly declined to less than 100 cases per year.[10] Minnick and Raman (2014) argue that this decline is significantly associated with a drop in household investors' equity holdings. Further, Kisling and Barinka (2013) justify this decline with the fact that retail investors become less important to the investor base. Panel B categorizes split events by listing exchange. Around 40, 5, and 55 percent of splits are conducted by NYSE, AMEX, and NASDAQ listed firms, respectively. Panel C categorizes split events by splitting factor and shows that the overwhelming majority of firms use 1.5:1 to 2:1 splitting factors. Panel D reports the percentage of stock split firms that belong to each size and MTBV quintile. More than 60 percent of stock splits are conducted by firms within the top two size and MTBV quintiles. These statistics are consistent with those of Desai and Jain (1997) and Byun and Rozeff (2003).

3.2. Measuring discretionary accruals and real activities management

Our methodology in estimating discretionary accruals is similar to that of Guo, Liu, and Song (2008). We first measure total accruals (*T_ACR*) using balance sheet and income statement variables as change in noncash current assets, minus changes in current liabilities excluding short-term debt and taxes payable, minus depreciation. Then, we estimate discretionary accruals as the residual, $\varepsilon_{i,t}$, from the modified version of Jones (1991) model as described in Dechow, Sloan,

[10] Both the economic and the statistical significance of our results do not change when excluding split cases conducted after 2008, these results are available upon request.

and Sweeney (1995).[11] Specifically, for each calendar year and two-digit SIC-code, we estimate the following model:

$$T\_ACR_{i,t} = \beta_1 1/TA_{i,t-1} + \beta_2 \left(\Delta SALE_{i,t} - \Delta REC_{i,t}\right) + \beta_3 PPE_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $T\_ACR_{i,t}$ is the firm's total accruals. $TA_{i,t-1}$ is the firm's lagged total assets. $\Delta SALE_{i,t}$ is the firm's change in sales. $\Delta REC_{i,t}$ is the firm's change in accounts receivable. $PPE_{i,t}$ is the firm's property, plant, and equipment. $\varepsilon_{i,t}$ is a random error term. We follow the accounting literature in scaling all variables by lagged total assets. Collins, Pungaliya, and Vijh (2016) assert that models based on Jones (1991) to estimate discretionary accruals are misspecified for quarterly data as they do not account for growth. Although we are using annual data, our descriptive statistics presented later show that our split portfolios have similar growth characteristics measured by market-to-book ratio. Further, because stocks in all our portfolios are split stocks, which have high growth (more than 70 percent are in the top two MTBV quintiles), the effect of growth on our portfolios is expected to be homogeneous, leaving our portfolio ranking unchanged. As an extra precaution, we replicate all our tests using growth and performance matched measures of discretionary accruals.[12] Results using the growth/performance-adjusted discretionary accruals are similar to our reported results.[13]

Roychowdhury (2006) shows that manipulative firms can use sales manipulation and/or discretionary expenses manipulation to manage earnings. While firms can manipulate sales through excessive discounts and lenient credit terms, they can manipulate discretionary expenses

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[11] Guo, Liu, and Song (2008) used the original Jones (1991) model. The version of Jones (1991) model used here takes into account the possibility of managers' earnings management through exercising their discretion over revenues. For more details, please see Dechow, Sloan, and Sweeny (1995).

[12] For each firm/ year, we first estimate discretionary current accruals as the residual from the modified Jones (1991) model in equation (1). Then, within each year and 2-digit SIC-code, we form five quintile ranks based on sales growth and returns on assets (ROA), resulting in 25 unique portfolios within each year/industry. Adjusted discretionary accruals is then calculated as the difference between firm/year discretionary accruals and the median discretionary accruals of the performance/growth matched portfolio for the same year and industry.

[13] These results are available upon request.

through cutting research and development (R&D) costs; sales, general, and administrative (SG&A) costs; and/or advertising expenses. In this study we focus on RAM using sales manipulation.[14] Firms that give excessive discounts and/or lenient credit terms have unusually low cash flows from operations. We calculate abnormal cash flows as the residual, $\varepsilon_{i,t}$, from the model of Roychowdhury (2006). Specifically, for each calendar year and two-digit SIC code, we estimate the following model,

$$\mathrm{CFO}_{\mathrm{i,t}} = \alpha_0 + \alpha_1(1/\,\mathrm{TA}_{\mathrm{i,t-1}}) + \beta_1 \mathrm{SALE}_{\mathrm{i,t}} + \beta_2\,\Delta\, SALE_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $CFO_{i,t}$ is cash flows from operating activities, $TA_{i,t-1}$ is the firm's lagged total assets, $SALE_{i,t}$ is the firm's net sales, and $\Delta\, SALE_{i,t}$ is the firm's change in sales. We follow the accounting literature in scaling all variables by lagged total assets.

3.3. Portfolios formation

The idea that the standalone estimates of pre-split discretionary accruals or RAM are not sufficient to fully differentiate between optimistic and opportunistic/overoptimistic managers is the core of our portfolio formation.[15] This idea is based on prior literature that shows that, although standalone earnings management could be a positive signal (Louis and Robinson, 2005), combining accruals management and RAM has always been perceived as an aggressive strategy that has negative long-term consequences on firm value (Cohen and Zarowin, 2010; and Kothari, Mizik, and Roychowdhury, 2012). This literature assumes that managers with strong incentives to aggressively inflate their earnings might find themselves constrained by the limited discretionary

[14] More recent accounting literature focuses on abnormal discretionary expenses as a less confounding measure of RAM; for this purpose, in a separate test we also add real activities management using discretionary expenses. Results are also consistent with our conjectures. When firms inflate their pre-split earnings using accruals and RAM using both sales manipulation and discretionary expenses manipulation, post-split long-term returns are significantly lower than those reported for firms that use less complex schemes, i.e., the higher the capacity of pre-split earnings management the lower the post-split returns. Results of this test are reported in the robustness section.

[15] The robustness of this idea is further tested on section 4.2.6.

accruals capacity; hence, those managers are expected to support their accruals management with real activities management. Similarly, Hsieh, Bedard, and Johnstone (2014) show that overconfident managers participate more in aggressive accruals and real activities management. Following this literature, we use pre-split accruals and RAM to disentangle optimistic splits and overoptimistic/opportunistic splits.

To rank stock splits according to the degree of earnings management, we double sort based on pre-split discretionary accruals and abnormal cash flows terciles.[16] We first create three RAM terciles, following the conjecture of Cohen and Zarowin (2010) and Kothari, Mizik, and Roychowdhury (2012), that RAM is more value-destroying than accruals management. Second, inside each RAM tercile, we rank firms based on discretionary accruals. However, ranking based on RAM is more linear than ranking based on discretionary accruals. With RAM, firms with the most positive (negative) abnormal cash flow are considered the less (most) likely to have managed earnings whereas with discretionary accruals, although the most suspicious earnings management is usually associated with positive discretionary accruals, both extremes are considered suspicious. So we assume that the most conservative stocks would be associated with around zero discretionary accruals and the least conservative stocks would be associated with high positive pre-split discretionary accruals. This ranking results in nine portfolios; M1: M9; where portfolio M1 includes firms in the bottom discretionary accruals and RAM terciles prior to a stock split, and portfolio M9, at the other extreme, includes firms in the top discretionary accruals and RAM terciles prior to a stock split. It is worth noting that our portfolio formation does not assume specific sequential use of earnings management methods (Zang, 2012). We report descriptive statistics for the nine portfolios M1: M9 in Table 2.

[16] Discretionary accruals and abnormal cash flows are measured for the calendar year preceding the stock split announcement year.

[Please insert Table 2 here]

Statistics in Table 2 show that portfolios at the bottom of the earnings management ladder (M1:M3) are not significantly different from those at the top (M7:M9) with respect to size, growth, sales, pre-split returns, splitting factors, or split announcement returns. [17] Descriptive statistics show that portfolios at the top of the earnings management ladder (M7:M9) have relatively higher leverage and lower profitability (ROA) than those on the bottom of the earnings management ladder (M1:M3). So, even with aggressive earnings management, firms in portfolios M7:M9 could not match the genuinely high earnings reported by optimistic firms. Further, high leverage could partially explain management engagement in aggressive accounting tactics, possibly to meet certain earning targets.[18] Further, the average pre-split price for stocks in portfolio M9 is $53.3, which is lower than the average pre-split price for stocks in portfolio M1, which is $60.5. This difference rules out the possibility that the return reversal following portfolio M9 splits is due to improved price informativeness, which might have been the case if portfolio M9 stocks have significantly higher pre-split prices (Chan et al. (2017)). Our main contribution is that portfolios at the two ends of the earnings management ladder have strikingly different post-split abnormal returns. Descriptive statistics in Table 2 show that, while portfolio M1 has a one-year buy-and-hold positive abnormal return of 11.9 percent, portfolio M9 has a one-year buy-and-hold negative abnormal return of -7.1 percent.

[17] Please notice that the pattern in abnormal cash flows (*Acfo*) and discretionary accruals (*Dacc*) is there by design. Our methodology dictates that portfolio M1 for example has around zero discretionary accruals and positive abnormal cash flows. On the other extreme, portfolio M9 should have positive discretionary accruals and negative abnormal cash flows.

[18] Our later results (reported in Table 8 and discussed in section 4.2.4) lend some support to this assumption. Leverage is positively associated with the likelihood of conducting over-optimistic/opportunistic splits (portfolio M9 splits).

Our untabulated Pearson correlation matrix shows a significant positive correlation between one-year post-split BHAR and abnormal cash flows one year before the split event.[19] Firms that aggressively manage earnings using RAM experience lower post-split returns. The one-year post-split BHAR is also negatively correlated with pre-split discretionary accruals, so managing accruals prior to stock splits also results in post-split return reversals. However, our later results show that the stand-alone return predictability of components of earnings management weakens/vanishes in the regression tests. Further, split announcement returns measured by the cumulative abnormal returns ($CAR_{-1,+1}$) are not significantly correlated with pre-split earnings management using either discretionary accruals or RAM.

4. Analysis and results

4.1. Stock split announcement returns

In this section, we test the link between pre-split earnings management and split announcement returns using both portfolio and regression analysis. If investors use earnings management estimates to assess the legitimacy of a stock split signal, then announcement returns should be asymmetrical among portfolios M1:M9. We calculate cumulative abnormal returns (CAR) of firm *i* in the split announcement period as follows,

$$\mathrm{CAR}_{-\mathrm{k},+\mathrm{k}} = \sum_{t-k}^{t+k}(R_{i,t} - E(R_{i,t})), \tag{3}$$

where $R_{i,t}$ is the stock *i* daily actual returns and $E(R_{i,t})$ is the daily expected returns of stock *i* calculated using the market model estimated over the six-month period that ends ten days before the split announcement day. Table 3 reports CARs for the nine portfolios as well as for the entire sample of stock splits.

[Please insert Table 3 here]

[19] Pearson correlation coefficients table is available upon request.

For the entire split sample, the average $CAR_{-1,+1}$ is 2.8 percent, which is significant at the 1 percent level, while the average $CAR_{-5,+5}$ is 3 percent, which is also significant at the 1 percent level. Our results show that $CAR_{-k,+k}$ is significantly positive for all nine portfolios. Buying stock splits one day before the split announcement day can achieve 180 to 330 basis points in abnormal returns over a three-day holding period. These results are similar to GMT (1984) and Louis and Robinson (2005) who report a three-day split announcement returns of 3.4 percent and 2.4 percent, respectively. According to GMT (1984), these strong positive announcement returns may act as a motive for overvalued firms to split their stocks without having any positive information to reveal. An interesting observation is that, within each RAM tercile, announcement returns are higher for the top discretionary accruals group.[20] This result is consistent with Louis and Robinson (2005). Investors seem to perceive splits that are accompanied with high discretionary accruals as a signal of managerial optimism. However, these differences ultimately vanish in our regression tests. A possible explanation for this is the control for growth (*MTBV*), which might explain a significant part of the amount of firm's current accruals (Collins, Pungaliya, and Vijh, 2016).

Results in Table 3 lend support to the idea that a positive split announcement's abnormal returns are not related to pre-split earnings management. Investors do not recognize a firm that combines the split signal with aggressive earnings management signal as an overvalued firm. Instead, our results show that CARs are relatively higher for portfolio M9 ($CAR_{-1,+1}$ = 3.3 percent) as compared to portfolio M1 ($CAR_{-1,+1}$ = 1.9%), i.e., there is preliminary evidence that investors possibly associate these splits with managerial optimism. To formally test the relation between pre-split earnings management and split announcement returns, we run the following model,

[20] For example, among portfolios M1:M3, portfolio M3 has the highest announcement returns. Similarly, among portfolios M4:M6, portfolio M6 has the highest announcement returns, and among portfolios M7:M9, portfolio M9 has the highest announcement returns.

$$CAR_{i,-k,+k} = \propto + \beta_1 Portfolio\ M1 - M9 + \beta_2 Pre - Split\_Returns_i + \beta_3 Size_i + \beta_4 MTBV_i + \beta_5 Split\_Price_i + \beta_6 Leverage_i + \beta_7 Splitting\ factor_i + \varepsilon_i \quad (4)$$

where $CAR_{i,-k,+k}$ is stock split announcement cumulative abnormal returns. In Table 4, in specifications (1) and (2), the dependent variable is $CAR_{-1,+1}$, in specifications (3) and (4), the dependent variable is $CAR_{-3,+3}$, and in specifications (5) and (6), the dependent variable is $CAR_{-5,+5}$. To account for the possible momentum impact of the pre-split price run-up, we control for $Pre\text{-}split\_returns_i$, which is the raw stock returns during the 12-month period prior to the split announcement month, following GMT (1984). To account for the impact of information asymmetry on a split announcement return, we control for $Size_i$, which is the decile rank based on total assets. $MTBV_i$ is the decile rank based on market-to-book value. We control for $Split\_price_i$ which is the price on the day immediately following the day on which the split becomes effective, to account for market reaction to specific price range (Fernando, Krishnamurthy, and Spindt, 1999). $Leverage_i$ is the ratio of long-term debts to total assets. We control for $Splitting\ factor_i$, which is the stock split factor, to account for the possibility that some managers use splitting factors to signal their private information.[21] $Acfo_i$ is the pre-split estimate of abnormal cash flows. $Dacc_i$ is the pre-split estimate of discretionary accruals. *Portfolio_M1-M9* is a dummy variable that equals to “1” if the firm belongs to portfolio M1, and “0” if it belongs to portfolio M9.

[Please insert Table 4 here]

Table 4 reports coefficient estimates of the split announcement return regressions. While there is a negative association between abnormal cash flow ($Acfo_i$) and split announcement return, discretionary accruals ($Dacc_i$) are not significantly related to split announcement *CARs*. This result is in contrast to Louis and Robinson (2005) who show a positive association between pre-split

[21] Controlling for split factor accounts for argument of Baixauli (2007) that split abnormal announcement returns are reported only when split factor is greater than two.

accruals and announcement return. One possible explanation is that we use annual estimates of discretionary accruals for the period 1988–2011 whereas they use quarterly estimates for the period 1990-2002, which are misspecified particularly for high-growth split firms, according to Collins, Pungaliya, and Vijh (2016). In Table 4, columns 2, 4, and 6, we report results for specifications comparing the two extreme earnings management portfolios (including a dummy variable *Portfolio_M1-M9*, hence using around 20 percent of the sample). These results also do not show any significant relation between pre-split earnings management and split announcement returns. Investors seem to react more positively to splits announced by small (*Size*) and value stocks (*MTBV*). Announcement returns are positively related to splitting factors. This finding is consistent with McNichols and Dravid (1990) who assert that investors seem to perceive splitting factors as a signal of the nature of managers' private information.

Results in this section show that investors do not use pre-split earnings management estimates to assess stock split announcements. Because the majority of stock splits are believed to be conducted by firms with good earnings potential, investors seem to naively consider that all stock splitters are undervalued. By doing so, investors push some "already overvalued" stocks to deviate even more from their fundamental values. These results are consistent with Bardos, Golec, and Harding (2011) who show that investors are misled by inflated earnings at the time of the announcement and react positively to the component of the favorable earnings surprise, which will subsequently be restated. Similarly, our results indicate that, for some splits, investors are misled by pre-split earnings management and react positively to false splits, which will subsequently be followed by return reversals.

4.2. Long-term abnormal returns following stock splits

Literature on measuring long-term abnormal returns proposes two broad methodologies: buy and hold abnormal returns (BHAR) and calendar-time portfolio. On the one hand, Lyon, Barber, and Tsai (1999) and Loughran and Ritter (2000) prefer the BHAR methodology. On the other hand, Fama (1998) and Mitchell and Stafford (2000) strongly favor the calendar-time portfolio approach. In this study, we investigate long-term returns of our portfolios using both methodologies.[22]

4.2.1. Buy and hold abnormal returns

In this section, we investigate long-term returns of our portfolios using the BHAR method. We calculate the one-year post-split BHAR as follows:

$$BHAR_i = \prod_{t=1}^{T}\left[1 + R_{i,t}\right] - \prod_{t=1}^{T}\left[1 + E\left(R_{i,t}\right)\right], \tag{5}$$

where $R_{i,t}$ is the actual return of stock i on month t and $E(R_{i,t})$ is the expected return for security i on month t. Expected return $E\left(R_{i,t}\right)$ is measured as the return for size and book-to-market matched portfolios. To form reference portfolios, we first assign split firms to size and book-to-market quintiles based on NYSE breakpoints.[23] Then we compare the stock price performance of split firms to 25 portfolios formed on size and book-to-market quintiles using NYSE breakpoints (Fama and French, 1992 and 1993). [24] Stock splits usually follow unusually high price run-ups (Byun and Rozeff, 2003); therefore, many stock splits could be significantly driven by market-wide and/or industry-wide movements.[25] To account for the possibility that post-split returns are driven by the

[22] To eliminate the effect of split announcement returns, our window for measuring long-term returns starts with the split effective date instead of the split announcement date.

[23] Following Fama and French (1997) we calculate book equity as total shareholders' equity, minus preferred stocks (when available), plus deferred taxes (when available), plus investment tax credit (when available), plus post-retirement benefit liabilities (when available). Book-to-market equity is calculated as the ratio of fiscal year end book equity divided by market capitalization of common stock at calendar year end.

[24] Similar results are acquired using the S&P500 composite index and also the Fama-French 48 industry returns.

[25] For example, as shown in Table 1, good market years like 1998 have a high number of stock splits.

persistence or reversal of such movements, we report results using two additional proxies for expected returns: returns for the S&P500 composite index and the Fama-French 48 industry returns.[26]

Table 5 presents the BHAR for each of the nine portfolios as well as the return differential between portfolios M1 and M9.[27]

[Please insert Table 5 here]

Results reported in Table 5 show that post-split returns are negatively associated with pre-split earnings management. The one-year BHAR using size and book-to-market reference portfolios ($BHAR_{ref}$) for portfolio M1 is 5.5 percent. This high and positive return is in stark contrast to portfolio M9 which has a $BHAR_{ref}$ of -16 percent. $BHAR_{ref}$ is positive and significant for portfolios M1-M3, is not significantly different from zero for portfolios M4-M6, and is significantly negative for portfolios M7-M9.

Tests using market returns ($BHAR_{sp500}$) and firm-specific industry returns ($BHAR_{ind}$) as proxies for expected returns yield similar results. The average one-year $BHAR_{sp500}$ is 11.9 percent for portfolio M1 and is significantly negative at -7.1 percent for portfolio M9. $BHAR_{ind}$ is 5.5 percent for portfolio M1 and is significantly negative at -5.8 percent for portfolio M9. Our results show that the industry-adjusted measure, $BHAR_{ind}$, is the most conservative measure of abnormal returns. This result is consistent with the notion that returns around stock splits could be significantly driven by industry-wide trends. These results show that neither size and book-to-market reference portfolios nor market returns or industry returns explain the significantly large difference in post-split returns between portfolios M1 and M9.

[26] Industry-adjusted buy and hold abnormal return is calculated by subtracting from the split firm return the average return for the associated Fama-French 48 industry.
[27] In a separate test, we also measure return differentials between portfolios with higher degrees of earnings management and portfolio M9; results of these tests are available upon request.

4.2.2. Regression analysis

In this section, we investigate the long-term returns of portfolio M1 (supposedly, optimistic splits) and portfolio M9 (supposedly, overoptimistic/opportunistic splits), using the regression method. We estimate the following cross-sectional predictive regression of post-split long-term returns:

$$BHAR_i = \propto + \beta_1 Portfolio\ M1 - M9 + \beta_2 Pre - Split\_Returns_i + \beta_3 Size_i + \beta_4 MTBV_i \quad (6)$$

$$+ \beta_5 Split\_Price_i + \beta_6 Leverage_i + \beta_7 Splitting\ factor_i + \varepsilon_i$$

where the dependent variable $BHAR_i$ is the post-split one-year BHAR. $BHAR_{ref}$ is used in specifications (1) and (2), $BHAR_{sp500}$ is used in specifications (3) and (4), and $BHAR_{ind}$ is used in specifications (5) and (6). Since under-reaction is expected to be more prominent for smaller firms with higher information asymmetry, we control for firm *Size*. To control for the impact of firm growth on long-term performance, we control for *MTBV*. To control for the possibility of managers' use of splitting factors to signal their long-term expectations, we control *for splitting factor*. Control variables are defined in the manner explained earlier.

[Please insert Table 6 here]

Coefficient estimates in columns 2, 4, and 6 in Table 6 show that investigating pre-split earnings management can help predict future returns. The average return differential between portfolio M1 and portfolio M9 (coefficient estimate of *portfolio M1-M9*) ranges between 4.4 percent and 10 percent after controlling for size, growth, momentum, split price, leverage, and splitting factor. Coefficients of *pre-split_returns* show that the higher the price run-up prior to the split announcement, the lower the post-split returns. Post-split returns are higher for firms with high growth opportunities, where the coefficients of *MTBV* in Table 6 are positive and significant at the 1 percent level. *Splitting factor* does not seem to provide any predictive power for post-split long-term abnormal returns. Because we do not assume linear relations neither between discretionary accruals on their own nor abnormal cash flows on their own and long-term returns, insignificant coefficients of *Acfo* and *Dacc* are not surprising. This result is consistent with Kothari, Mizik, and Roychowdhury (2012) who find evidence of long-term consistent negative returns associated with firms that concurrently manage earnings using both accruals and RAM during the pre-SEO periods.

4.2.3. Calendar time portfolios

In this section, we estimate the monthly returns of a zero-investment portfolio that buys portfolio M1 and sells portfolio M9 short. We use the calendar-time methodology to compute average monthly returns of a portfolio of stocks formed at the end of each month. To adjust returns for risk exposure and stock characteristics, we estimate intercepts from the four-factor model that includes the Fama-French (1993) factors and the Carhart (1997) momentum factor as follows:[28,29]

$$R_t = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Momentum_t + \epsilon_t, \qquad (7)$$

where R_t is the monthly return of our calendar month portfolio at month *t*, $RMRF_t$is the month *t* value-weighted market return minus the risk-free rate, and the terms SMB_t (small minus big), HML_t (high minus low), and $Momentum_t$ are the month *t* returns on the zero-investment factor-mimicking portfolios designed to capture size, book-to-market, and momentum effects, respectively. Table 7 reports the estimated intercepts (Alphas) from the four-factor model.

[Please insert Table 7 here]

Results reported in panel A of Table 7 (column 1) show that, after controlling for risk factors and momentum, the equally (value) weighted zero-investment portfolio that buys M1

[28] Fama-French (1993) three factor-model alphas are separately estimated. These results are available upon request.
[29] Stock splits usually follow periods of exceptionally high stock returns. The Carhart (1997) momentum factor has been added to take into consideration the possibility of the persistence of pre-split good returns.

stocks and sells short M9 stocks would gain 100 (90) basis points per month for a 12-month holding period. Results for 24- and 36-month portfolios (columns 2 and 3) indicate that most of the reported abnormal returns are achieved within the first 12 months following the split announcement month. These results lend support to our earlier BHAR results. However, implementing this trading strategy depends primarily on the availability of earnings management estimates before the split announcement date. So any stock split announced before the release of a firm's annual report cannot be a part of this trading strategy. Otherwise, our results might suffer from a look-ahead bias.

Although most firms file their annual reports within 45 days of the fiscal year end, the federal securities laws require large accelerated filers, accelerated filers and non-accelerated filers to file form 10-k no later than within 60, 75, and 90 days of the fiscal year end, respectively.[30] To insure the full implementation of our proposed trading strategy, we report alphas for the zero-investment portfolios that exclude splits announced within 45, 60, and 75 days of the fiscal year end, respectively.[31] Results reported in panels B through D of Table 7 confirm that the trading strategy proposed in this paper is implementable and ensures that the calendar month portfolio results are not disrupted by a look-ahead bias. Excluding split announcements within 45 days or 60 days of the fiscal year end does not hinder the profitability of the calendar month zero-investment portfolio. A 12-month zero-investment portfolio that buys M1 stocks and sells short M9 stocks would gain an average of 90 basis points per month. We note that this positive return is mostly due to the large and significant positive returns of M1 stocks. Therefore, short selling constraints would not impair the profitability of this trading strategy. It is worth noting that,

[30] Please see more details on http://www.sec.gov/answers/form10k.htm

[31] The overwhelming majority of stock split firms are classified as large accelerated filers (please see Tables 1 and 2). We also report results excluding splits announced within 75 days of fiscal year end as an extra caution.

although this zero-investment portfolio is constructed using the top and bottom earnings management portfolios (a total of 1,059 stock splits), statistically significant results (economically less significant though) are acquired when using the top and bottom three earnings management portfolios (a total of 3,434 stock splits). Further, given that CRSP dataset has over 20,000 unique stock split announcements, the top and bottom portfolios in that population are consisting of a reasonably large number of events.

Figure 1 provides a graphic depiction of the performance of portfolios M1 and M9. This figure presents the value-weighted cumulative abnormal return (CAR) for the 24-month period following the split announcement month (month "0").

[Please insert Figure 1 here]

Figure 1 shows a divergence between portfolios M1 and M9 that happens around the sixth month following the split announcement. During the 24-month post-split period, portfolio M1 experiences a 20 percent positive CAR, whereas portfolio M9 experiences a -21 percent CAR during the same period. Calendar month portfolio results reported in this section show that this divergence could be translated into a profitable and fully implementable trading strategy.

In summary, regression as well as portfolio analysis provide evidence that the market underreacts to stock splits in portfolio M1 (supposedly, optimistic splits). Markets, on the other hand, overreact to stock splits in portfolio M9 (supposedly, overoptimistic/opportunistic splits).

4.2.4. Stock splits: alternative explanations

The main idea of this paper is that some managers (splitters in portfolio M9) combine earnings management and splits for signaling purposes. However, signaling is just one reason to conduct a stock split. The literature provides several alternative explanations such as boosting liquidity, changes in household and institutional ownership, and catering (Minnick and Raman

(2014)). In this section, we test the possibility that portfolio M9 splits are motivated by these alternative hypotheses.

First, we investigate the possibility that portfolio M9 splits are explained by the drop in households' ownership (the increase in institutional ownership).[32] If portfolio M9 is a mere reflection of poor (good) governance and/or the increase (decline) in stock splits occurrences associated with increasing households' (institutional) equity ownership, then we would expect a significant association between the likelihood of these splits and households' and/or institutional equity ownership. We define aggregate households' ownership as the total equity holdings owned by U.S. households. We proxy for the aggregate level of institutional ownership by the equity ownership of U.S. domestic financial institutions.[33] We also control for firm-level institutional ownership.[34] Second, we investigate the possibility that portfolio M9 splits are explained by firms desire to boost stock liquidity. We use the decimalization in 2001 as an exogenous shock to stock liquidity to test this hypothesis. If liquidity explains splits in portfolio M9, then these splits should experience a much larger decline, as compared to other splits, in the post-2001 period.

Next, we investigate the possibility that portfolio M9 splits are explained by the catering hypothesis. Minnick and Raman (2014) show that the catering premium has declined from 1983 to 2009. If splits in portfolio M9 are motivated by firms' desire to cater to investors' demand for cheaper stocks, then the likelihood for these splits are expected to observe a larger decline over the sampling period as compared to other splits. Lastly, we further investigate our conjecture that portfolio M9 splits are best described by the signaling hypothesis. Our signaling assumptions posit

[32] An earlier work by Mukherji, Kim, and Walker (1997) shows that, although stock splits increase number of both individual and institutional shareholders, the percentage of equity held by institutions does not change significantly following a stock split.

[33] Data for the aggregate levels of ownership are acquired from the Federal Reserve Statistical Release, Z.1. Flow of funds (annual) accounts, http://www.federalreserve.gov/releases/z1. Households' ownership is FL153064105, and U.S. domestic financial sector ownership is FL793064105.

[34] Firm-level institutional ownership data are acquired from Thomson Reuters.

that portfolio M9 includes opportunistic split in addition to overoptimistic ones. Opportunistic splitters, who are aware that their stocks are over-valued, are expected to try to reap personal benefits before a market correction takes place. In that context, a split can be seen as a false signal to delay such correction (Guo, Liu, and Song [2008]). In order to further investigate this conjecture, we test CEOs trading behavior around split announcements. Results of testing the abovementioned alternative hypotheses are presented in Table 8.

[Please insert Table 8 here]

The dependent variable in all of the logistic regression models in Table 8 is a dummy variable that equals to "1" if a split belongs to portfolio M9 and "0" otherwise. Specification (1) tests the liquidity hypothesis. To capture the 2001 decimalization liquidity shock, we control for *Post-2001*, which is a dummy variable that equals to "1" for the years after 2001. The coefficient estimate of *Post-2001* is not statistically significant, which rules out the possibility that M9 splits are conducted by firms with a desire to improve stock liquidity. Specification (2) in Table 8 tests the possible impact of households' and institutional ownership. The coefficient estimates of household ownership (*Agg_household*), and institutional ownership (both on the aggregate-level, *Agg_institutional*, and on the firm-level, *Inst_ownership*) are not statistically different from zero.

Specification (3) in Table 8 tests the catering hypothesis. *Catering* is an ordinal variable that equals to "1" for the first year in our sample (1988). This variable captures the gradual decline of the catering premium over the sample period. The coefficient estimate of *Catering* is negative and statistically significant, indicating that the likelihood of portfolio M9 splits has declined over the overall sampling period. However, in specification (5), at which we also control for *Post_2001*, the coefficient estimate of *Catering* is not statistically significant. So, the decline, which is insignificant though, in the likelihood of portfolio M9 splits is probably more associated with the enhancing governance and manipulation detection following the SOX and/or tick size change of 2001 instead of with the gradual decline in the catering premium (Minnick and Raman, 2014) or the clientele effect (Lipson and Mortal, 2006). In specification (4) in Table 8, we investigate the false signal (opportunism) hypothesis by controlling for insider trading. *Net_insider_trading* is the difference between numbers of a CEO's buy-and-sell transactions conducted during the six months window around the split announcement date (i.e., Net-buyers (Net-sellers) have positive (negative) values of *Net_insider_trading*). The coefficient estimate of *Net_insider_trading* is significantly negative at the 10 percent level, indicating that net-sellers are more likely to conduct portfolio M9 splits. Our untabulated results show that most of this insider trading happens in the pre-split period, which rules out the possibility that it is driven by the improvement in informed trading following stock split events (Chan et al. [2017]). It is worth noting that this evidence is expected to be much stronger if one distinguishes between opportunistic and overoptimistic splits in portfolio M9. However, as we mentioned earlier, this distinction falls beyond the scope of this paper. Results in specification (5) in Table 8 lend further support to our signaling explanation. The coefficient estimates on factors that capture households' ownership, institutional ownership, liquidity, and catering alternative hypotheses are not statistically significant. However, the coefficient estimate of *Net_insider_trading* is statistically significant at the 5 percent level. These results are consistent with our conjecture that portfolio M9 is more likely to include firms that combine a split and earnings management for signaling purposes.

In the next three sections, we investigate three ideas that are essential to the interpretation of our results. First, we argue that the portfolio formation proposed in this paper can help explain some results in the prior literature. To test this conjecture, we investigate the persistence of our results in a subsample investigated in Byun and Rozeff (2003). Second, the portfolio formation proposed in this paper is based on the idea that the concurrent use of earnings management estimates is superior to the stand-alone use of separate estimates. We test this conjecture by investigating the stand-alone return predictability of earnings management estimates. Third, and most important, our interpretation of the dual use of the split signal and the earnings management signal is based on the notion that the split has an additional mispricing impact on top of that of earnings management. To further investigate this conjecture, we try to separate the price impact of the split signal from that of the earnings management signal.

4.2.5. Optimistic vs. overoptimistic/opportunistic splits in prior literature

We argue that extant studies of long-term returns following stock splits do not differentiate between optimistic splits and overoptimistic/opportunistic splits. The results reported in this paper are not unique to our sample. Instead, similar portfolio formation can be conducted to better explain results in prior studies. We replicate one of the tests in Byun and Rozeff (2003) who show that, during the 1991–1996 period, post-split abnormal returns are not significantly different from zero. [35] Our untabulated results show that, during 1991–1996, abnormal returns are not significantly different from zero for the entire sample of stock splits. However, when using the portfolio formation proposed in this study, we report significantly different returns for the portfolio M9 versus other stock splits. On one hand, portfolio M9 has an average one-year $BHAR_{ref}$ of -9.6 percent. On the other hand, all other splits have a 2.4 percent positive abnormal return during the same period. These results do not imply that Byun and Rozeff (2003) results were inaccurate. On the contrary, for the overall sample of splits, our results are consistent with theirs. However, this result suggests that estimates of earnings management might be an omitted variable in studying long-term returns following stock splits.

[35] We do not have data for earnings management to replicate FFJR (1969) or Desai and Jain (1997), who test splits during 1927-1950 and 1976-1991, respectively.

4.2.6. Standalone return predictability of earnings management estimates.

Our portfolio formation is based on the idea that the concurrent use of earnings management estimates is superior to the standalone use of separate estimates. To investigate the standalone return predictability of the pre-split discretionary accruals and RAM, we calculate the one-year post-split BHAR for different portfolios based on pre-split discretionary accruals and RAM, separately. For the purpose of completeness, we report results for three distinct earnings management portfolio rankings: tercile, quintile, and decile portfolios, respectively. However, to facilitate comparison with our baseline results, we focus our discussion on tercile ranking portfolios. *High* refers to firms with the most aggressive pre-split accruals management (RAM), consisting of splits in portfolio with the highest income increasing discretionary accruals (lowest abnormal cash flows). *Low* refers to firms with the least aggressive pre-split accruals management (RAM), consisting of splits in portfolio with the non-income-increasing/non-income-decreasing discretionary accruals (highest abnormal cash flows). The results of this test are reported in Table 9.

[Please insert Table 9 here]

Panel A of Table 9 reports $BHAR_{ref}$ for the top and the bottom earnings management portfolios. For the discretionary accruals tercile ranking portfolios, one-year $BHAR_{ref}$ of the most (least) aggressive portfolio is -7 percent (1 percent).The difference between $BHAR_{ref}$ of these two portfolios is statistically significant at the 1 percent level. We replicate the sub-periods of Green, Hand, and Soliman (2011), prior to 1996, 1997-2003, and 2004-2010, respectively. Our return differential results show that the accruals anomaly is persistent regarding stock splits. The difference in $BHAR_{ref}$ between the most and the least aggressive accruals management splits ranges between 6 percent and 8 percent, which is statistically significant during the three sub–

periods. These results (using tercile ranking) contrast the findings of Green, Hand, and Soliman (2011) who show that the accruals anomaly does not exist in the later sub-period. Louis and Robinson's (2005) explain this contradiction by pointing out that some managers try to combine accruals management with the split event to benefit from investors' positive reaction to this double-signaling tactic. This tactic could be fully legitimate for some managers; however, it could be an act of over-optimism or opportunism for others. Consequently, estimates of discretionary accruals surrounding stock splits could be, on average, more informative than those for the overall sample of stocks. It is worth noting that using quintile and/or decile rankings gives some support to the idea that the accruals anomaly vanishes in later periods (return differential is not statistically significant in the 2004-2010 sub-period). Much weaker results are reported for RAM tercile-ranking portfolios. The one-year $BHAR_{ref}$ of the most (least) aggressive portfolio is -9 percent (-3 percent). The difference between $BHAR_{ref}$ of these two portfolios is significant at the 1 percent level only for the overall sample of splits. However, the difference in $BHAR_{ref}$ between the most and the least aggressive RAM splits is not statistically significant during two of the three tested sub-periods (pre-1996 and 2004-2010).

To formally test the standalone return predictability of pre-split discretionary accruals and RAM, we run the following model:

$$BHAR_i = \propto + \beta_1 EM\_dummy + \beta_2 Pre - Split\_Returns + \beta_3 Size_i + \beta_4 MTBV_i \qquad (8)$$
$$+ \beta_5 Split\_price_i + \beta_6 Leverage_i + \beta_7 Splitting\ factor_i + \varepsilon,$$

where the dependent variable $BHAR_i$ is the post-split one-year $BHAR_{ref}$. In each specification, EM_dummy is a binary variable that takes the value of "1" if the firm belongs to the most aggressive earnings management portfolio, and "0" if it belongs to the least aggressive one. Specifications (1), (2), and (3) use splits on the top and bottom portfolios based on discretionary accruals with tercile, quintile, and decile ranking, respectively. Specifications (4), (5), and (6) use splits on the top and bottom portfolios based on RAM tercile, quintile, and decile ranking, respectively. Control variables are defined in the manner explained earlier. Results of OLS regression are reported in panel B of Table 9. Results on specifications (1) – (3) lend further support to the idea that discretionary accruals could aid post-split return predictability. For specifications (1) – (3), the coefficients of the *EM_dummy* is statistically significant at the 1 percent level. However, the return differential based on discretionary accruals ranking is economically much smaller than that reported based on our ranking which uses both accruals and RAM. Further, results on specifications (4) – (6), show that the return predictability of the RAM vanishes on the regression test. A possible explanation for this finding is that overoptimistic and/or opportunistic splitters might use RAM only as a supporting tool for accruals management instead of as a stand-alone method. Consequently, the use of RAM by overoptimistic/opportunistic splitters cannot be fully understood without studying its concurrent use side by side with accruals management. [36]

4.2.7. The separate signal of stock splits and earnings management

The dual use of split and earnings management as a false signal (as described in Guo, Liu, and Song (2008) and by portfolio M9 in this paper) is based on the notion that, when conducted by overoptimistic/opportunistic managers, a split has an additional signaling impact on top of the earnings management impact. To further investigate this conjecture, we try to separate the price impact of the split signal from that of the pre-split earnings management signal. Specifically, we compare long-term abnormal returns of a treatment group consisting of firms that conduct stock splits preceded by both aggressive accruals and RAM with those of a control group consisting of matched non-split firms with similar levels of earnings management.

[36] See among others: Baber, Fairfield, and Haggard (1991), Bushee (1998), Dechow and Skinner (2000), and Roychowdhury (2006).

Our treatment group (*Aggressive_Splits*) consists of firms that conduct stock splits preceded by aggressive accruals and RAM. We begin with the entire set of stock splits during 1988–2011 that has Compustat data available. Following Kothari, Mizik, and Roychowdhury (2012), we define "treatment firms" as split firms that have a one-year pre-split positive discretionary accruals and negative abnormal operating cash flows. This procedure results in 724 stock splits. We match each (*Aggressive_Split*) with a (*Aggressive_Non_Split*) based on size, MTBV, a two-digit SIC-code, year, discretionary accruals, and abnormal cash flows.[37]

[Please insert Table 10 here]

Results reported in panel A of Table 10 show that the treatment group (*Aggressive_Splits*) has negative one-year $BHAR_{ref}$ of -15.6 percent. This figure is significantly lower than the -9.6 percent reported for the control group (*Aggressive_Non_Splits*). Similar albeit less significant results are reported when using S&P 500 and Fama-French industry returns as expected returns. The $BHAR_{sp500}$ ($BHAR_{ind}$) for *Aggressive_Splits* is 7.9 percent (4 percent) lower than that of *Aggressive_Non_Splits*.

The difference in returns between *Aggressive_Splits* and *Aggressive_Non_Splits* captures the mispricing impact of stock split announcements. Our explanation of the dual signaling hypothesis would not be plausible if the post-split negative returns are fully explained by accruals and RAM. To formally test this conjecture, we run the following model,

$$BHAR_i = \alpha + \beta_1\, Aggressive\_Splitter + \beta_2 Pre-split\_returns_i + \beta_3 Size_i + \beta_4 MTBV_i + \beta_5 Leverage_i + \beta_6 Acfo_i + \beta_7 Dacc + \varepsilon_i, \quad (9)$$

[37] The matched control firm's size decile, MTBV decile, two-digit SIC-code, and year should be equal to those of the treatment firm. Further, the matched control firm's discretionary accruals and abnormal cash flows should be within 70 percent and 130 percent of those of the treatment firm. Our final treatment and control samples comprise 716 pairs of *Aggressive_Splits* and *Aggressive_Non_Splits*.

where the dependent variable $BHAR_i$ is the post-split one-year BHAR. $BHAR_{ref}$ is used in specifications (1) and (2), $BHAR_{sp500}$ is used in specifications (3) and (4), and $BHAR_{ind}$ is used in specifications (5) and (6). *Aggressive_Splitter* is a dummy variable that equals to "1" if the firm belongs to the treatment group (*Aggressive_Splits*) and "0" if it belongs to the control group (*Aggressive_Non_Splits*). Control variables are defined as explained earlier.

Regression results reported in panel B of Table 10 are consistent with the univariate test. Coefficients of the *splitter* dummy indicate that one-year post-split abnormal returns of *Aggressive_Splits* are significantly lower than those of *Aggressive_Non_Splits*. This difference in returns (which supposedly captures the stock split mispricing impact) is robust to using different measures of abnormal returns and to controlling for size, BTMV, momentum, leverage, accruals, and real activities management.

5. Additional robustness tests

5.1. Earnings management through cutting discretionary expenses

The idea that the more aggressive the pre-split earnings management, the more likely the split is classified as overoptimistic/opportunistic is key to our findings. So far, we present results that support this idea using two forms of earnings management: discretionary accruals and real activities management using sales manipulation. We test the robustness of this idea further by adding another layer of earnings management: RAM through cutting discretionary expenses. Our arguments would assume that firms that concurrently participate in the three forms of earnings management should experience significantly lower post-split returns than firms with lower degree of pre-split earnings management.

Managing earnings by reducing R&D expenses has received special attention in the literature.[38] Roychowdhury (2006) defines discretionary expenses as the sum of R&D expenses, advertising expenses, and sales, general and administrative (SG&A) expenses. He argues that managers could reduce such expenses to achieve certain earnings targets. Following Roychowdhury (2006), for each calendar year and two-digit SIC-code, we estimate the following model,

$$DISEXP_{i,t} = \alpha_0 + \alpha_1 \left(1/TA_{i,t-1} \right) + \beta \, SALE_{i,t-1} + \varepsilon_{i,t}, \tag{11}$$

where $DISEXP_t$ is discretionary expenses for the year *t* scaled by total assets at the beginning of the year. TA_{t-1} is lagged total assets. $SALE_{t-1}$ is lagged sales scaled by total assets at the beginning of the year. For every firm-year, abnormal discretionary expenses is the actual *DISEXP* minus the "normal" *DISEXP*, calculated using estimated coefficients from the corresponding industry-year model. In addition to our nine regular earnings management portfolios, our results (untabulated) present abnormal returns for portfolio M10, consisting of firms with an evidence of aggressive accruals and RAM using both sales and discretionary expenses manipulation. These results lend further support to our conjectures. The $BHAR_{ref}$ for portfolio M10 is -22 percent compared to 5.5 percent (-16 percent) for portfolio M1 (M9). The same results are reported using the other proxies for abnormal returns, $BHAR_{sp500}$ and $BHAR_{ind}$. These results show that the higher the degree of the pre-split earnings management, the lower the post-split abnormal returns. In general, these results are consistent with the earnings management literature regarding the effect of earnings management aggressiveness on long-term returns.[39] Our results show that the most

[38] See for example, Baber, Fairfield, and Haggard (1991), and Bushee (1998).

[39] Teoh, Welch, and Wang (1998b) show that the worst post seasonal equity offerings (SEO) performance is reported for issuers with an unusually large income-increasing accounting adjustment prior to the offering. Teoh, Welch, and Wang (1998a) document that IPO issuers in the most aggressive quartile of earnings management have 20 percent lower three-year abnormal returns than IPO issuers in the most conservative quartile. Gong, Louis, and Sun (2008)

prominent negative (positive) post-split abnormal returns are reported for firms with the highest (lowest) degree of pre-split earnings management.

5.2. Long-term returns following stock splits in the prior literature

In this section, we investigate a number of arguments presented in the stock split literature. We test the profitability of portfolio M1-M9 in relation to dividends, size, growth, splitting factors, time, and institutional ownership.

Fama, Fisher, Jensen, and Roll (1969) argue that markets react positively to the dividends increase associated with stock splits, and when controlling for such dividends component, they do not find any informational content in stock splits. To show that our results are not presumed by dividends, we present our results in relation to dividends payment and change. The results in panels A and B of Table 11 show that the market underreacts (overreacts) to portfolio M1 (portfolio M9) regardless of whether the firm pays/simultaneously increases dividends or not, indicating that earnings management is not a mere reflection of dividends payment or change.

[Please insert Table 11 here]

Less information is available for small stocks. As a result, under-reaction is expected to be more prominent for smaller firms (Atiase, 1985; Lakonishok and Vermaelen, 1990; and Desai and Jain, 1997). Following the same intuition, we project that the overreaction to splits conducted by firms in portfolio M9 should also be more severe for smaller stocks. The results in panel C of Table 11 are consistent with this assumption. Among portfolio M9 stocks, smaller firms have a one-year $BHAR_{ref}$ of -19 percent as compared to -14 percent for larger firms.

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show that the negative association between pre-repurchase discretionary accruals and post-repurchase abnormal returns is largely driven by firms reporting the largest income-decreasing abnormal accruals. Further, Allen, Larson, and Sloan (2013) show that extreme accruals exhibit a high frequency of subsequent reversals that predict future accruals, earnings, and stock returns.

Fama and French (1992) and Lakonishok, Shleifer, and Vishney (1994) show that value stocks outperform glamour stocks. Inversely, Desai and Jain (1997) show that value stocks underperform glamour stocks for stock splits. The results reported in panel D of Table 11 show that, for portfolio M1, the one-year $BHAR_{ref}$ is -2.3 percent (9.4 percent) for value (glamour) stocks. For portfolio M9, the one-year $BHAR_{ref}$ is -22 percent (-12 percent) for value (glamour) stocks. These results are similar to Desai and Jain (1997), indicating that, for stock splits, value stocks underperform glamour stocks.

McNichols and Dravid (1990) assert that the splitting factor is a self-selection decision made by managers in order to signal their private information. Our results in panel E of Table 11 do not show any clear relation between the profitability of the earnings management portfolio and splitting factors. This result is consistent with Desai and Jain (1997) and also with our regression analysis results. Further, Chen and Huang (2013) argue that the accruals anomaly regarding open-market repurchases has vanished after the SOX. Courteau, Kao, and Tian (2015) show that SOX has prompted firms to favor real activities manipulation over accruals manipulation. To examine whether our results are affected by SOX, we report abnormal returns for two sub–periods, 1988-1999 and 2000-2011 in panel F of Table 11. The profitability of the earnings management portfolio M1-M9 is statistically and economically significant in both periods, with evidence of increase towards the second half of our sample period.

Last firms with high institutional ownership are expected to have better governance than those with low institutional ownership. Panel G in Table 11 reports $BHAR_{ref}$ of splits conducted by firms with high (above median) and low (below median) levels of institutional ownership. For firms with high institutional ownership, portfolio M9 has an average $BHAR_{ref}$ of -5.6, which is less negative than firms with low institutional ownership, which has an average $BHAR_{ref}$ of -8.4 percent.

This difference could be explained by the role that institutions are playing to reduce managers' discretion in adopting aggressive earnings management tactics. However, the return differential between portfolio M1 and portfolio M9 for both high and low institutional ownership firms is very similar (around -21 percent), and is statistically significant at the 1 percent level. In summary, results in this section show that profitability of the earnings management portfolios of stock splits is robust in relation to size, growth, dividends, splitting factors, time, and institutional ownership.

6. Conclusion

Extant literature on long-term returns following a stock split ignores the existence of overoptimistic splitters and opportunistic splitters. These two types of splitters aggressively manage earnings and may split their stocks regardless of the fact that future earnings are not likely to be high enough to cover reversals. Our results provide evidence that many firms use stock split signals to support their inflated, rather than genuinely high, earnings. At stock split announcements, investors do not distinguish between these stocks and other stocks, so they react positively to both types. In the long-term, splits preceded by evidence of accruals and real activities management significantly underperform those not preceded by earnings management. Using both regression and portfolio tests, we find that pre-split earnings management negatively predicts long-term post-split returns.

A trading strategy of buying stocks with a low degree of pre-split earnings management and selling short stocks with a high degree of pre-split earnings management yields positive long-term abnormal returns of around 100 basis points per month for a 12-month holding period. Regression tests show that the effect of pre-split earnings management on post-split long-term abnormal returns is not predicted by the effect of past returns or of other stock characteristics such as size, growth, dividends, leverage, and splitting price and factor.

Our results contribute to the return predictability literature by showing that consideration of possible managerial incentives is mandatory for the study of long-term return predictability following stock splits. Our results also show that investors can use information on the concurrent use of accruals and RAM before stock splits to improve the predictability of long-term stock price performance. These results complement Louis and Robinson (2005) by showing that combining earnings management signals and split signals is not always a means of communicating reliable private information.

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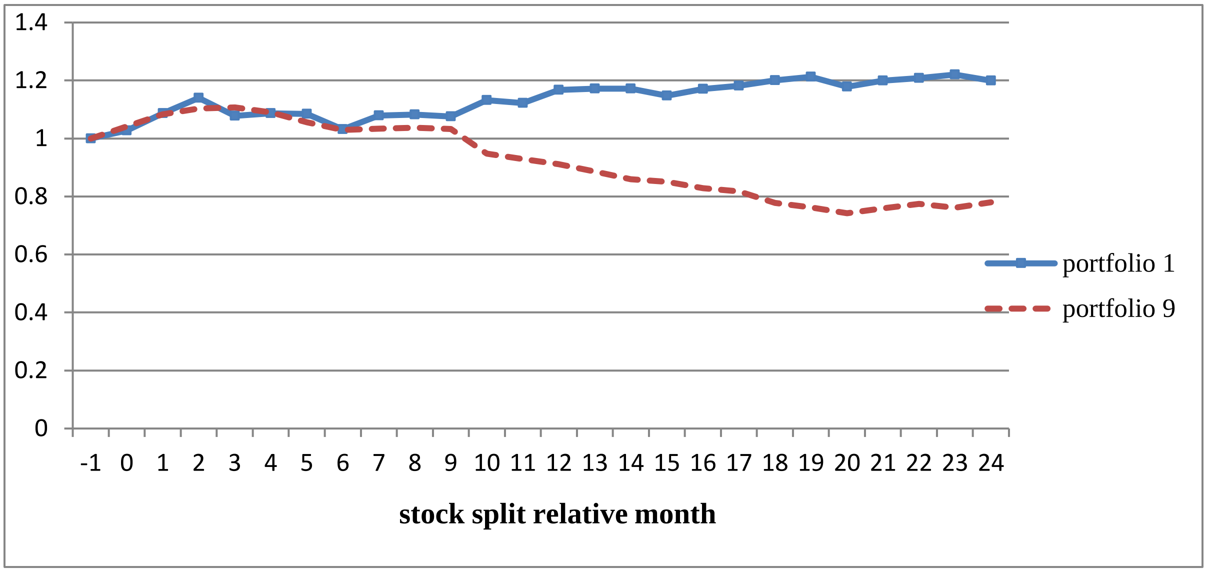

Figure 1. Value-weighted cumulative abnormal returns

This figure presents value-weighted cumulative abnormal returns following stock splits. Stock split month is month "0." We report monthly CARs for the 24-month post-split period.

Table 1. Stock splits 1988-2011

This table reports descriptive statistics for forward stock splits that took place during 1988-2011 for our final split sample of 5,155 split events. Panel A reports the number of stock splits per calendar year. Panel B categorizes stock splits by the listing exchange. Panel C categorizes stock splits by splitting factor. We also report the size and MTBV decile of stock split firms within each category in Panels A, B, and C. Panel D reports the number of stock split firms that belong to each quintile of firm size and MTBV.

Panel A. Stock splits per year 1988-2011

year	No.	Size decile	MTBV decile	year	No.	Size decile	MTBV decile
1988	23	6.4	6.5	*2000*	452	6.2	7.2
1989	149	5.6	6.5	*2001*	166	6.2	7.3
1990	126	6	7	*2002*	149	6.2	7
1991	170	5.7	7	*2003*	150	5.5	6.7
1992	275	6	6.7	*2004*	217	5.9	6.5
1993	282	5.9	6.7	*2005*	246	6.1	6.7
1994	233	5.9	6.7	*2006*	207	6.4	6.2
1995	326	5.9	7	*2007*	162	6.5	6.7
1996	422	5.7	6.9	*2008*	66	6.1	6.1
1997	426	6.2	6.8	*2009*	19	5.4	6.1
1998	411	6.3	6.8	*2010*	54	6.1	6.6
1999	351	6.4	7.2	*2011*	73	6.1	6.7

Panel B. Stock splits by listing exchange

Exchange	No.	%	Size Decile	MTBV decile
NYSE	2,030	39.4	7.5	6.6
AMEX	281	5.4	4.7	5.9
NASDAQ	2,844	55.2	5.2	7

Panel C. Stock splits by splitting factor.

Splitting factor	No.	%	Size Decile	MTBV decile
SF≤1.5 : 1	247	4.8	5.5	6
1.5:1< SF <2:1	1,737	33.7	5.5	6.6
SF = 2:1	2,755	53.4	6.4	7.1
SF > 2:1	416	8.1	6.6	6.2

Panel D. Percentage of stock splits in each size and MTBV quintiles.

	Q1	Q2	Q3	Q4	Q5
Size	2.04	10.03	26.62	32.06	29.25
MTBV	2.7	5.8	13.91	29.49	48.09

Table 2. Descriptive statistics for earnings management ranked portfolios of stock splits

Using double sorting based on abnormal cash flows and discretionary accruals we divide split firms into nine earnings management ranking portfolios M1:M9. M1 consists of firms with no evidence of accruals management or RAM one-year prior to their stock splits. M9 consists of firms with an evidence of both accruals management and RAM. *Total assets* and *Total Assets_Decile* are pre-split total assets and the decile rank based on total assets, respectively. *MTBV* and *MTBV_Decile* are pre-split market to book value and the decile rank based on market to book value, respectively. *Sales* is the net sales one year before the split year. *Splitting Factor* is the stock split splitting factor. *Leverage* is the ratio of long term debts to total assets. *Pre-Split_Price* is the stock price ten days prior to the split effective date. *Pre-Split_Returns* is the raw stock returns excluding dividends during the 12-month period prior to the split month. $CAR_{-1,+1}$ is the split announcement day cumulative abnormal returns calculated using the market model over the 3 days period t-1,t+1. *Post-Split_Returns* is the raw stock returns in the 12-month period following the split month. $BHAR_{sp500}$ is the one year post split buy and hold abnormal returns, where the expected returns is the return for the S&P500 index. All return variables are presented in percentages. *ROA* is the returns on assets one year before the split year. *Dacc* is the pre-split discretionary accruals estimated as the residuals from the modified Jones (1991) model, and *Acfo* is the pre-split abnormal cash flow estimated as the residuals from the Roychowdhury (2006) model**.** Reported values are means. All variables are winsorized at the 1 and 99 percent levels.

	Earnings management ranked portfolios M1-M9								
	M1	M2	M3	M4	M5	M6	M7	M8	M9
No. Of Obs.	421	692	646	649	554	518	577	460	638
Size (Mill.)	2,849	2,429	1,866	3,603	2,649	2,514	4,190	2,435	2,097
Size_Decile	6.2	5.8	5.8	6.6	6	6	6.6	5.8	5.8
MTBV	5.9	6.5	7	3.9	4.9	5	3.7	4.6	5.4
MTBV_Decile	7.5	7.5	7.6	6.5	6.9	6.9	6	6.3	6.8
Sales (Mill.)	1,795	1,719	1,057	2,353	1,783	1,666	2,612	1,840	1,385
Splitting Factor	2	1.9	1.9	1.9	1.9	1.9	1.9	1.9	1.9
Leverage	0.12	0.11	0.10	0.17	0.14	0.15	0.20	0.14	0.15
Pre-Split_Price	60.5	56.6	59.6	53.5	49.9	53.2	49.5	49.8	53.3
Pre-Split_Returns (%)	90	106	120	67	90	97	70	104	120
$CAR_{-1,+1}$ *(%)*	1.9	2.6	2.8	1.8	2.8	2.6	2.3	2.8	3.3
Post-Split_Returns (%)	16	10	3	12	11	6	7	5	-4
$BHAR_{sp500}$ *(%)*	11.9	3	7.5	3.3	3	4.4	1.1	2	-7.1
ROA (%)	9.9	9.4	9.3	7.1	7.6	8.1	4.6	5.10	5.1
Dacc	0.00	-0.27	0.34	0.00	-0.24	0.27	0.00	-0.24	0.31
Acfo	0.35	0.41	0.46	0.08	0.09	0.09	-0.08	-0.18	-0.26

Table 3. Stock splits announcement returns based on earnings management portfolios

This table reports cumulative abnormal returns (CAR) for the entire group of stock splits as well as for the nine earnings management ranking portfolios. M1 is a portfolio consisting of firms with the lowest degree of pre-split discretionary accruals and RAM. M9, on the other extreme, is a portfolio with the highest degree of pre-split discretionary accruals and RAM. CAR is calculated as $\sum_{t-k}^{T+k}(R_{i,t} - E(R_{i,t}))$ for three different announcement periods, t-1:t+1, t-3:t+3 and t-5:t+5, where $E(R_{i,t})$ is the stock expected returns estimated using the market model. P-values are between parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% levels, respectively. All variables are winsorized at the 1 and 99 percent levels.

Portfolio	No. of Obs.	CAR $_{-1,+1}$	CAR $_{-3,+3}$	CAR $_{-5,+5}$
M1	421	1.9***	2.1***	1.4***
		(0.000)	(0.000)	(0.000)
M2	692	2.6***	2.6***	2.7***
		(0.000)	(0.000)	(0.000)
M3	646	2.8***	2.7***	2.8***
		(0.000)	(0.000)	(0.000)
M4	649	1.8***	2.2***	1.9***
		(0.000)	(0.000)	(0.000)
M5	554	2.8***	2.7***	2.9***
		(0.000)	(0.000)	(0.000)
M6	518	2.6***	3.1***	3.4***
		(0.000)	(0.000)	(0.000)
M7	577	2.3***	2.4***	2.2***
		(0.000)	(0.000)	(0.000)
M8	460	2.8***	2.9***	3.0***
		(0.000)	(0.000)	(0.000)
M9	638	3.3***	2.9***	2.6***
		(0.000)	(0.000)	(0.000)
Portfolio M1-M9		-1.4***	-0.8***	-1.2***
		(0.000)	(0.000	(0.000)
All	5,155	2.8***	3.1***	3.0***
		(0.000)	(0.000)	(0.000)

Table 4. Regression of stock split announcement returns

This table reports coefficient estimates of the OLS regression of stock split announcement returns on earnings management variables and various control variables. Dependent variable is stock split announcement cumulative abnormal return (CAR). For specifications 1 and 2, dependent variable is $CAR_{-1,+1}$. For specifications 3 and 4, dependent variable is $CAR_{-3,+3}$. For specifications 5 and 6, dependent variable is $CAR_{-5,+5}$. *Portfolio M1-M9* is a dummy variable which takes the value "0" if the firm belongs to portfolio M9 and "1" if it belongs to portfolio M1. *Acfo* is the pre-split abnormal cash flow estimated as the residuals from the Roychowdhury (2006) model. *Dacc* is the pre-split discretionary accruals estimated as the residuals from the modified Jones (1991) model. *Pre-Split_Returns* is the raw stock returns during the 12-month period prior to the split month. *Size* is decile rank based on total assets. *MTBV* is the decile rank based on market to book value. S*plit_price* is the price in the day just following the split effective day. *Leverage* is the ratio of long-term debts to total assets. *Splitting Factor* is the stock split splitting factor. Coefficients are estimated using industry fixed effects. P-values are between parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% levels, respectively. All variables are winsorized at the 1 and 99 percent levels.

	$CAR_{-1,+1}$		$CAR_{-3,+3}$		$CAR_{-5,+5}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.042^{***}	0.042^{***}	0.051^{***}	0.046^{**}	0.063^{***}	0.084^{***}
	(0.000)	(0.009)	(0.000)	(0.035)	(0.000)	(0.003)
Portfolio M1-M9		-0.002		-0.004		-0.003
		(0.692)		(0.567)		(0.689)
Acfo	-0.002^{*}		-0.005^{***}		-0.005^{**}	
	(0.084)		(0.009)		(0.025)	
Dacc	-0.000		-0.001		0.000	
	(0.967)		(0.395)		(0.830)	
Pre-Split_Returns	0.001	0.003^{**}	0.003^{***}	0.007^{***}	0.002^{**}	0.005^{**}
	(0.136)	(0.036)	(0.000)	(0.000)	(0.014)	(0.050)
Size	-0.006^{***}	-0.006^{***}	-0.009^{***}	-0.005^{**}	-0.011^{***}	-0.009^{***}
	(0.000)	(0.000)	(0.000)	(0.012)	(0.000)	(0.002)
MTBV	-0.001^{*}	-0.002^{*}	-0.001^{*}	-0.003^{**}	-0.002^{**}	-0.008^{***}
	(0.054)	(0.081)	(0.086)	(0.040)	(0.012)	(0.001)
Split_price	0.001^{***}	0.000^{***}	0.001^{***}	0.000^{**}	0.001^{***}	0.001^{***}
	(0.000)	(0.001)	(0.000)	(0.036)	(0.000)	(0.000)
Leverage	0.005	0.009	0.015	-0.013	0.012	-0.021
	(0.443)	(0.524)	(0.118)	(0.505)	(0.293)	(0.430)
Splitting Factor	0.007^{***}	0.007	0.011^{***}	0.009	0.010^{***}	0.005
	(0.000)	(0.215)	(0.000)	(0.230)	(0.002)	(0.583)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3,448	705	3,448	705	3,448	705
Adjusted R2 (%)	4.2	5.7	5.0	5.9	4.6	7.5

Table 5. Earnings management ranked portfolios Post-split buy and hold abnormal returns

This table reports the average buy and hold abnormal returns for the nine earnings management-ranked portfolios M1:M9, where portfolio M1 includes stock splits with the lowest degree of pre-split earnings management, and portfolio M9 includes stock splits with the highest degree of pre-split earnings management. We also report the return differential between portfolio M1 and M9, *M1-M9*. For each stock, buy and hold abnormal return is measured as $BHAR_i = \prod_{t=1}^{250}[1 + R_{i,t}] - \prod_{t=1}^{250}[1 + E(R_{i,t})]$, where $R_{i,t}$ is the total rate of return of stock *i* on day *t* and $E(R_{i,t})$ is the expected return for each security *i* on day *t*. $BHAR_{ref}$ is the one-year buy and hold abnormal returns, where expected return is the return for size and book-to-market reference portfolio. $BHAR_{sp500}$ is the one-year buy and hold abnormal returns, where expected return is the return for S&P500 composite index. $BHAR_{ind}$ is the one-year buy and hold abnormal returns, where expected return is the return for firm-specific Fama-French 48 industry. P-values are reported in Parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All variables are winsorized at the 1 and 99 percent levels.

	one-year post-split abnormal returns		
Portfolio	$BHAR_{ref}$	$BHAR_{sp500}$	$BHAR_{ind}$
M1	5.5*	11.9***	5.5*
	(0.051)	(0.000)	(0.070)
M2	6.9***	3.00	-2.6
	(0.000)	(0.161)	(0.247)
M3	4.3*	7.5**	5.9*
	(0.097)	(0.013)	(0.056)
M4	-1.7	3.3*	1.2
	(0.261)	(0.056)	(0.533)
M5	-3.8*	3.0	2.1
	(0.056)	(0.169)	(0.370)
M6	-3	4.4	2.2
	(0.286)	(0.139)	(0.518)
M7	-4.5***	1.1	-2.8
	(0.006)	(0.593)	(0.220)
M8	-6.5**	2.00	-1.6
	(0.018)	(0.452)	(0.636)
M9	-16***	-7.1***	-5.8**
	(0.000)	(0.003)	(0.017)
Portfolio M1-M9	22***	19.1***	11.2***
	(0.000)	(0.000)	(0.003)

Table 6. Cross section predictive regression of post-split long-term stock returns

This table reports coefficient estimates from predictive regressions of post-split long-term returns on pre-split earnings management and control variables. We use three different dependent variables to represent post-split long-term returns. $BHAR_{ref}$ is the one-year buy and hold abnormal returns, where expected return is the return for size and book-to-market reference portfolio. $BHAR_{sp500}$ is the one-year buy and hold abnormal returns, where expected return is the return for S&P500 composite index. $BHAR_{ind}$ is the one-year buy and hold abnormal returns, where expected return is the return for firm-specific Fama-French 48 industry. *Portfolio M1-M9* is a dummy variable which takes the value "0" if the firm belongs to portfolio M9 and "1" if it belongs to portfolio M1. *Acfo* is the pre-split abnormal cash flow estimated as the residuals from the Roychowdhury (2006) model. *Dacc* is the pre-split discretionary accruals estimated as the residuals from the modified Jones (1991) model. *Pre-split return* is the raw stock returns excluding dividends during the 12-month period prior to the split month. *Size* is decile rank based on total assets. *MTBV* is the decile rank based on market to book value. *Split_price* is the price in the day just following the split effective day. *Leverage* is the ratio of long-term debts to total assets. *Splitting Factor* is the stock split splitting factor. Coefficients are estimated using industry fixed effects. P-values are between parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% levels, respectively. All variables are winsorized at the 1 and 99 percent levels.

	$BHAR_{ref}$		$BHAR_{sp500}$		$BHAR_{ind}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.396***	-0.514***	-0.478***	-0.645***	-0.466***	-0.682***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Portfolio M1-M9		0.089**		0.100**		0.044**
		(0.026)		(0.035)		(0.048)
Acfo	0.015		0.021		0.011	
	(0.217)		(0.190)		(0.455)	
Dacc	-0.017*		-0.010		0.012	
	(0.075)		(0.398)		(0.281)	
Pre-split return	-0.029***	-0.053***	-0.007	-0.034***	-0.001	-0.021*
	(0.000)	(0.000)	(0.204)	(0.010)	(0.802)	(0.099)
Size	0.009*	-0.000	0.000	-0.005	0.001	-0.003
	(0.089)	(0.976)	(0.928)	(0.697)	(0.785)	(0.796)
MTBV	0.053***	0.056***	0.074***	0.077***	0.060***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Split price	-0.002***	-0.001	-0.000	-0.000	0.000	0.001
	(0.000)	(0.248)	(0.509)	(0.926)	(0.654)	(0.409)
Leverage	0.109**	0.177	0.210***	0.453***	0.191***	0.506***
	(0.044)	(0.123)	(0.003)	(0.001)	(0.004)	(0.000)
Splitting Factor	0.011	0.059	0.012	0.068	0.018	0.074
	(0.445)	(0.185)	(0.534)	(0.202)	(0.323)	(0.154)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3,448	705	3,448	705	3,448	705
Adjusted R^2	5.9	10.8	4.8	8.9	3.9	7.1

Table 7. Four-factors alphas for calendar month zero-investment portfolios

This table reports the four factors model alphas estimated as the intercepts from the four factors model consisting of Fama-French (1993) three-factors and Carhart (1997) momentum factor. We estimate alphas for the zero-investment portfolio of buying portfolio M1 and selling portfolio M9 short. We report four different post-split holding periods, 12-month, 24-month, 36-month and 12-month starts 6 months after the split month. We report both equally-weighted and value-weighted portfolios. Panel A reports results for portfolios formed with all stock splits. Panel B reports results excluding splits announced within 45 days of the fiscal year end. Panel C reports results excluding splits announced within 60 days of the fiscal year end. Panel D reports results excluding splits announced within 75 days of the fiscal year end. Estimates are reported in % per month. P-values are reported in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All variables are winsorized at the 1 and 99 percent levels.

Portfolio M1-M9	+1,+12	+1,+24	+1,+36	+6,+18
		Panel A. All splits.		
Equally-weighted	1^{***}	0.7^{***}	0.4^{*}	0.8^{**}
	(0.003)	(0.002)	(0.070)	(0.025)
Value-weighted	0.9^{**}	0.7^{**}	0.7^{**}	1^{**}
	(0.034)	(0.039)	(0.017)	(0.019)
		Panel B. All splits excluding cases announced within 45 days of fiscal year end.		
Equally-weighted	0.9^{**}	0.8^{***}	0.5^{**}	0.8^{**}
	(0.036)	(0.009)	(0.048)	(0.026)
Value-weighted	0.9^{*}	0.6^{*}	0.8^{**}	1^{**}
	(0.057)	(0.076)	(0.013)	(0.032)
		Panel C. All splits excluding cases announced within 60 days of fiscal year end.		
Equally-weighted	0.9^{**}	0.8^{**}	0.5^{*}	0.7^{**}
	(0.032)	(0.011)	(0.057)	(0.042)
Value-weighted	0.9^{*}	0.6	0.8^{**}	0.8^{*}
	(0.054)	(0.109)	(0.016)	(0.088)
		Panel D. All splits excluding cases announced within 75 days of fiscal year end.		
Equally-weighted	0.8^{*}	0.5	0.7^{**}	0.8^{*}
	(0.100)	(0.165)	(0.026)	(0.088)
Value-weighted	0.7^{*}	0.6^{**}	0.4	0.6^{*}
	(0.081)	(0.037)	(0.132)	(0.075)

Table 8. Different explanations of stock splits

This table reports coefficient estimates of the logistic regression models of the likelihood of firms to participate in portfolio M9 splits. Dependent variable is a dummy variable that equals to "1" if the split belongs to portfolio M9, and "0" otherwise. *Post_2001* is a dummy variable that equals "1" for the years after 2001, and "0" otherwise. *Agg_household* is the aggregate value of equity owned by U.S. household. *Agg_institutional* is the aggregate value of equity owned by U.S. domestic financial institutions. *Inst_ownership* is the percentage of a firm's stocks owned by institutions. *Net_insider_trading* is the number of a CEO's buy transaction minus sell transactions during the six-month period surrounding a split announcement date. *Acfo* is the pre-split abnormal cash flow estimated as the residuals from the Roychowdhury (2006) model. *Dacc* is the pre-split discretionary accruals estimated as the residuals from the modified Jones (1991) model. *Pre-split return* is the stock raw returns excluding dividends during the 12-month period prior to the split month. *Size* is decile rank based on total assets. *MTBV* is the decile rank based on market to book value. *Split_price* is the price in the day just following the split effective day. *Leverage* is the ratio of long-term debts to total assets. *Splitting Factor* is the stock split splitting factor. P-values are between parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% levels, respectively. All variables are winsorized at the 1 and 99 percent levels.

	(1)	(2)	(3)	(4)	(5)
Constant	-1.511***	-1.218***	-1.274***	-1.573	-1.012**
	(0.000)	(0.004)	(0.002)	(0.000)	(0.032)
Post_2001	-0.169				0.110
	(0.224)				(0.757)
Agg_household		-0.000			-0.000
		0.381			0.485
Agg_institutional		0.000			0.000
		0.940			(0.542)
Inst_ownership		0.031			0.030
		(0.901)			(0.902)
Catering			-0.028**		-0.057
			(0.018)		(0.245)
Net_insider_trading				-3.571*	-3.983**
				(0.056)	(0.038)
Acfo	-2.069***	-2.092***	-2.087***	-2.065***	-2.081***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dacc	1.499***	1.493***	1.504***	1.493***	1.499***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pre-split return	0.036	0.038	0.035	0.038	0.038
	(0.128)	(0.108)	(0.132)	(0.103)	(0.104)
Size	-0.020	-0.031	-0.030	-0.017	-0.034
	(0.608)	(0.449)	(0.465)	(0.673)	(0.408)
MTBV	-0.020	-0.021	-0.021	-0.019	-0.022
	(0.516)	(0.492)	(0.490)	(0.535)	(0.476)
Split price	-0.005	-0.002	-0.003	-0.006	-0.002
	(0.209)	(0.616)	(0.458)	(0.139)	(0.596)
Leverage	1.090***	1.102***	1.090***	1.118***	1.129***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Splitting Factor	-0.189	-0.166	-0.170	-0.192	-0.159
	(0.186)	(0.242)	(0.230)	(0.176)	(0.262)
Industry FE	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3,448	3,448	3,448	3,448	3,448
- Log likelihood	1,015	1,013	1,013	1,014	1,010

Table 9. Standalone return predictability: Discretionary accruals vs. RAM

This table reports buy and hold abnormal returns ($BHAR_{ref}$) of portfolios of splits ranked based on pre-split earnings management. Panel A reports results for tercile, quintile, and decile ranked portfolios, respectively. Panel B reports OLS regression of the determinants of one-year post-split $BHAR_{ref}$. EM_dummy is earnings management dummy that takes the value of "1" if the firm belongs to the *High* earnings management portfolio and "0" if it belongs to the *Low* earnings management portfolio. In panel B. the sample that is used in each model is highlighted in the column heading. Other control variables are defined in the same manner explained earlier. P-values are between parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% levels, respectively.

Panel A. BHARs of discretionary accruals and RAM ranked portfolios

	Dacc									*Acfo*								
	Tercile rank			Quintile rank			Decile rank			Tercile rank			Quintile rank			Decile rank		
No. of Obs.	2,039	2,173	4,212	1,217	1,304	2,521	601	651	1,252	1,637	1,620	3,257	972	942	1,914	488	451	939
$BHAR_{ref}$	High	Low	H-L	High	Low	H-L	High	Low	H-L	High	Low	H-L	High	Low	H-L	High	Low	H-L
All	-0.07	0.01	-0.08***	-0.09	0.01	-0.09***	-0.13	0.02	-0.15***	-0.09	-0.03	-0.06***	-0.12	-0.01	-0.10***	-0.17	-0.4	-0.13***
			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)
Y<1996	-0.03	0.03	-0.06***	-0.03	0.03	-0.06***	-0.08	0.04	-0.12***	-0.06	-0.02	-0.04	-0.07	-0.01	-0.06	-0.5	0.03	-0.08
			(0.000)			(0.000)			(0.004)			(0.205)			(0.267)			(0.396)
1997-2003	-0.11	-0.04	-0.06*	-0.14	-.04	-0.09**	-0.19	-0.01	-0.18***	-0.16	-0.05	-0.11***	-0.19	-0.02	-0.17***	-0.25	-0.08	-0.17***
			(0.064)			(0.027)			(0.000)			(0.000)			(0.000)			(0.005)
2004-2010	-0.04	0.03	-0.08***	-0.03	0.00	-0.03	-0.03	0.01	-0.04	-0.02	0.02	-0.04	-0.02	0.01	-0.04	-0.06	0.00	-0.06
			(0.009)			(0.428)			(0.408)			(0.171)			(0.340)			(0.244)

Panel B. OLS regression: determinants of post-split BHAR

	(1) top and bottom *Dacc* terciles	(2) top and bottom *Dacc* quintiles	(3) top and bottom *Dacc* deciles	(4) top and bottom *Acfo* terciles	(5) top and bottom *Acfo* quintiles	(6) top and bottom *Acfo* deciles
Constant	-0.21***	-0.18***	-0.09	-0.35***	-0.44***	-0.53***
	(0.000)	(0.002)	(0.270)	(0.000)	(0.000)	(0.000)
EM_dummy	-0.06***	-0.06***	-0.09***	0.00	0.02	0.02
	(0.000)	(0.002)	(0.001)	(0.916)	(0.345)	(0.613)
Pre-Split_Returns	-0.03***	-0.04***	-0.09***	-0.04***	-0.03***	-0.03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
Size	0.00	0.00	0.00	0.00	0.01*	0.01
	(0.645)	(0.796)	(0.573)	(0.171)	(0.098)	(0.171)
MTBV	0.04***	0.04***	0.03***	0.04***	0.05***	0.06***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Split_price	-0.00***	-0.00***	-0.00	-0.00***	-0.00***	-0.00*
	(0.000)	(0.008)	(0.122)	(0.003)	(0.008)	(0.097)
Leverage	0.13***	0.12**	0.09	0.13**	0.17**	0.18*
	(0.007)	(0.044)	(0.209)	(0.017)	(0.025)	(0.079)
Splitting Factor	-0.00	-0.00	-0.00	0.00	-0.01	-0.01
	(0.505)	(0.740)	(0.865)	(0.957)	(0.567)	(0.461)
No. of Obs.	3,652	2,165	1,057	2,844	1,640	774
Adjusted R2	5.0	5.0	7.6	5.5	6.0	7.7

Table 10. Post-split long-term stock returns and the effect of stock splits

This table compares the long-term abnormal returns of the treatment group (*Aggressive_Splits*) and the matched control group (*Aggressive_Non_Splits*) in Panel A. Panel B reports coefficient estimates from predictive regressions of post-split long-term returns for the treatment group (*Aggressive_Splits*) and the control group (*Aggressive_Non_Splits*). Dependent variable in models (1) and (2), $BHAR_{ref}$, is the one-year buy and hold abnormal returns, where expected return is the return for size and book-to-market reference portfolio. Dependent variable in models (3) and (4), $BHAR_{sp500}$, is the one-year buy and hold abnormal returns, where expected return is the return for S&P500 composite index. Dependent variable in models (5) and (6), $BHAR_{ind}$, is the one-year buy and hold abnormal returns, where expected return is the return for firm-specific Fama-French 48 industry. *Aggressive_Splitter* is a dummy variable which equals "1" if the firm belongs to the treatment group (*Aggressive_Splits*) and equals "0" if it belongs to the control group (*Aggressive_Non_Splits*). *Pre-split return* is the raw stock returns excluding dividends during the 12-month period prior to the split month. *Size* is decile rank based on total assets. *MTBV* is the decile rank based on market to book value. *Leverage* is the ratio of long-term debts to total assets. *Acfo* is the pre-split abnormal cash flow. *Dacc* is the pre-split discretionary accruals. Coefficients are estimated using industry fixed effects. P-values are reported in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% levels, respectively. All variables are winsorized at the 1 and 99 percent levels.

Panel A. Post-split abnormal returns of *Aggressive_Splits* and *Aggressive_Non_Splits*

	Treatment (*Aggressive_Splits*)	Control (*Aggressive_Non_Splits*)	Difference
$BHAR_{ref}$	-15.6***	-9.6***	-5.9*
	(0.000)	(0.001)	(0.088)
$BHAR_{sp500}$	-17.7***	-9.8***	-7.9**
	(0.000)	(0.001)	(0.024)
$BHAR_{ind}$	-13.7***	-9.6***	-4.0
	(0.000)	(0.001)	(0.226)

Panel B. OLS regression: determinants of post-split abnormal returns.

	$BHAR_{ref}$		$BHAR_{sp500}$		$BHAR_{ind}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.10***	0.13**	-0.10***	-0.05	-0.10***	-0.06
	(0.000)	(0.027)	(0.000)	(0.453)	(0.000)	(0.291)
Aggressive_Splitter	-0.06*	-0.10***	-0.08**	-0.12***	-0.04	-0.09***
	(0.088)	(0.006)	(0.024)	(0.001)	(0.226)	(0.007)
Pre-split return		-0.00		-0.00		-0.00*
		(0.317)		(0.120)		(0.090)
Size		-0.01		0.02*		0.03**
		(0.763)		(0.061)		(0.034)
MTBV		-0.07***		-0.02*		-0.02
		(0.000)		(0.081)		(0.153)
Leverage		0.13		0.13		0.08
		(0.150)		(0.150)		(0.331)
Acfo		0.07***		0.09***		0.05*
		(0.009)		(0.003)		(0.056)
Dacc		0.01		0.02		0.01
		(0.676)		(0.348)		(0.588)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	1,349	973	1,349	973	1,349	973
Adjusted R^2	1.0	4.9	1.0	4.0	0.1	2.4

Table 11. Robustness tests

This table reports the one-year buy and hold abnormal returns ($BHAR_{ref}$) for portfolio M1, M9 and M1-M9. Panel A reports returns for dividend paying stocks and non-dividend paying stocks. Panel B reports returns for firms that increase dividends simultaneously with splits versus firms that do not. Panel C reports returns for large versus small stocks. Large (small) stocks are firms with above (below) median total assets at the split year. Panel D reports returns for glamour versus value stocks. We define glamour (value) stocks as firms with above (below) median market to book value. Panel E reports returns for stock splits with a 2:1 splitting factor versus all other stock splits. Panel F reports returns for splits that took place during 1989-2000 versus splits that took place during 2001-2011. Panel G reports returns for splits conducted by firms with high (above median) and low (below median) institutional ownership. Estimates are reported in percentages. P-values are reported in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively. All variables are winsorized at the 1 and 99 percent levels.

Panel A. Long-term buy and hold post-split returns by dividends paying			
	$BHAR_{ref}$		
	M1	M9	M1-M9
Dividends payer	8***	-9***	17.5***
	(0.010)	(0.000)	(0.000)
Non-dividend payer	2.6	-21***	23.6***
	(0.593)	(0.000)	(0.000)
Panel B. Long-term buy and hold post-split returns by *Dividends change*			
Dividend increase	4.8*	-15***	19.8***
	(0.100)	(0.000)	(0.000)
Non-dividend increase	14.8	-25***	39.8***
	(0.117)	(0.000)	(0.000)
Panel C. Long-term buy and hold post-split returns by *size*			
Small firms	5.4	-19***	24.5***
	(0.311)	(0.000)	(0.000)
Large firms	5.6*	-14***	19.6***
	(0.081)	(0.000)	(0.000)
Panel D. Long-term buy and hold post-split returns by *MTBV*			
Value stocks	-2.3	-22***	19.7***
	(0.540)	(0.000)	(0.000)
Glamour stocks	9.4**	-12***	21.4***
	(0.016)	(0.000)	(0.000)
Panel E. Long-term buy and hold post-split returns by *Splitting Factor*			
Split factor=2:1	5.3	-18***	23.5***
	(0.153)	(0.000)	(0.000)
Split factors ≠2:1	5.7	-15***	20.7***
	(0.186)	(0.000)	(0.000)
Panel F. Long-term buy and hold post-split returns by *Time*			
1988-1999	1.6	-14***	15.6***
	(0.713)	(0.000)	(0.000)
2000-2011	9.5***	-19***	28.5***
	(0.004)	(0.000)	(0.000)
Panel G. Long-term buy and hold post-split returns by *Institutional ownership*			
High inst. ownership	16.2***	-5.6**	21.8***
	(0.000)	(0.048)	(0.000)
Low inst. ownership	13.0	-8.4*	21.4***
	(0.105)	(0.054)	(0.010)